Technology Clustering: The Case of Greece

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Abstract—**In the globalization era, economic research has consistently shown that innovation effects tend to be clustered. Greece is among the oldest members of the E.U., one of the laggards in productivity and competitiveness in the wider E.U. and ranks very low in attracting foreign investments. In this paper, the various sectors of economic activity in Greece have been assembled into clusters presenting similar technology and growth characteristics which have a significant influence upon the productivity and competitiveness of the economy, by applying the Cluster Analysis methodology. In this way, the twenty-one sectors of economic activity are divided into three main sectors (i.e. primary, secondary, and tertiary) which are, in general terms, consistent with the structure of the total economy. Finally, some comments are made concerning policy issues for Greece.**

I. Introduction

Recent research has consistently shown that innovation activities in the European Union (E.U.) tend to be clustered [1]. For instance, cooperative relationships with regard to R&D between sectors or organizations belonging to the same sector are a good example [2]. There is also an emerging literature stressing the importance of the regional dimension of innovation. In this context, an important finding of empirical research is that in several countries innovations of a certain kind are concentrated in specific clusters [3].

This situation implies that regional productivity of technology and local levels of research are important determinants for clustering [4]. Consequently, the clustering of industries regarding their technology characteristics is of great interest. After all it is well known that innovation is probably the most important determinant of the process of technological change, whereas technological change itself is, in turn, extremely crucial for economic growth and for determining the standard of living in the long run.

However, despite these findings, very few researchers have studied the clustering of sectors and what this implies about technology and structural changes within an economic system. Consequently, it would be of great interest to investigate whether structural changes in different sectors tend to cluster, i.e. to form groups of sectors sharing similar technology and growth characteristics. In this context, we investigate the case of Greece, since the enlargement of the European Union (E.U) to the East will create a new allocation of resources and factors such as productivity of technology will play a decisive role for competitiveness in this area.

Since the mid 1990s, the Greek economy experienced strong growth, closing the gap vis-à-vis the E.U.-15. Actually, over the 1995-2005 period, Gross Domestic Product (G.D.P.) growth averaged 3.7% per year following a strong macroeconomic adjustment: the governmental deficit fell from 16% of G.D.P. to 5.5% since 2000 and inflation from around 20% to 3.5 %. In addition, some exogenous factors (e.g. Athens Olympics, etc) also contributed to strong growth. However, the country continues to be one of the laggards within the E.U. as it ranked last among E.U. members in Research and Development (R&D) expenditures [5] and very low in terms of growth in Total Factor Productivity T.F.P. [6].

The primary sector in Greece accounts for about 8.2% of the Gross National Product (G.N.P.), the secondary sector accounts for 21.6% and the tertiary sector accounts for 70.2%. Consequently, Greece has a sectoral structure which corresponds to a modern economy [7]. However, unemployment in the country is high; imbalances in employment opportunities may well arise between the east and west of the country as well as among the different sectors. Moreover, the share of high productivity small and medium companies appears to be low; the size of the unofficial economy is very big and competition from other European cities and economies is likely to intensify.

However, against this background, Greece has considerable potential for growth in a number of sectors [7]. Greece needs clear strategic planning to take advantage of the opportunities eastward expansion of the E.U. is bringing. In fact, Greece has considerable potential for development in its role as gateway to the eastern part of the enlarged E.U. and, of course, the Middle East. However, fulfilling this role will require strategic responses from the Greek government. In particular, there is a need for developing a strategic vision for linking economic and technological planning. The government should monitor the impact of E.U. enlargement on the Greek economy and develop a clear analysis of role that the various clusters play for Greece within E.U.

The purpose of the present paper is to group the twenty-one sectors of economic activity in Greece, into clusters of sectors sharing similar characteristics regarding technological change and growth. Regardless of the clusters specified, the behavior of different sectors within a cluster must be as similar as possible, while the behavior of sectors that do not belong to the same cluster must be as different as possible. To this end, the paper uses the clustering analysis methodology which offers a reliable quantitative framework.

If clustering really matters, this will certainly have implications for the structural characteristics of the economy. Obviously, the identification of poorly performing clusters of economic activity within the Greek economy has significant policy implications. For instance, the analysis pinpoints the industries forming a cluster, the performance of which is poor and needs enhancement. On the other hand, the Greek government might wish to subsidize changes in a certain cluster and our analysis indicates each cluster's characteristics.

II. METHODOLOGY

A general question in applied economics is how to organize observed data into meaningful structures and clustering has been used since long for grouping together entities with similar characteristics. Nowadays, it has acquired increasing attention as a solution to the complexity related to voluminous datasets. The main reason for its increased significance and convenience is that it relies on creating natural groups in the existing data rather than classifying them on the basis of some externally imposed criteria.

These clusters presumably reflect some mechanism at work in the domain from which data are drawn; the mechanism causes some units of the cluster to bear a stronger resemblance to one another than they do to the remaining units [8]. The method's flexibility is its main advantage. The methodology can be applied to a very wide range of cases, e.g. [9]-[11]. Clearly, the flexibility of the method and of the algorithms used explains the great diversity of its applications.

Consequently, cluster analysis, introduced in Tryon [12], refers to an exploratory data analysis tool which aims at sorting different data into groups in a way that the degree of association between two objects is maximal if they belong to the same group and minimal otherwise. So, cluster analysis can be used to discover structures in data where similar records are in the same group, and groups are as different as possible from each other [13].

Reviews of Clustering Algorithms have been provided by various researchers (e.g. [13], [14]). However, the algorithms available differ in how they compute the distance between the two clusters. We use the Euclidean distance as a measure of similarity, which is the most commonly chosen type of distance [14]. Note that Euclidean (and squared Euclidean) distances are usually computed from raw data. The Euclidean distance is the geometric distance. It is computed as:

$$\text{distance}\,(x,y) = \{ \textstyle\sum_i \ (x_i - y_i)^2 \}^{1/2} \qquad (1)$$

There exist several algorithms (e.g. Nearest Neighbor, Furthest Neighbor, Centroid, Median, Group Average, Ward's, and *K*-Means) for grouping observations from a multivariate dataset into clusters of similar points. In the *K*-Means method [15], the formation of clusters begins with an initial partition then uses a search algorithm to test other partitions to identify the one with the least error. The *K*-means method is the most commonly used algorithm in this type of investigations. Also, it has a very important advantage, that the distance between any two objects is not affected by the addition of new objects to the analysis, which may be outliers. It was chosen because it is effective in using a heterogeneous high-dimensional multivariate data set to create a manageable set of homogeneous classes which could be employed for issues of economic policy [15].

In *K*-means the observations are divided into *K* clusters in such a way that the objective function, i.e. the total sum of squared Euclidean distances between observations and their respective cluster centroids is minimized. The *K*-means algorithm minimizes the squared error function. The objective function is:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \left\| x_i^{(j)} - c_j \right\|^2 \qquad (2)$$

where $\left\| x_i^{(j)} - c_j \right\|$ is the distance measure between a data point $x_i^{(j)}$ and the cluster centre c_j, is an indicator of the distance of the *n* data points of each cluster from their respective cluster centers.

The number of clusters *K* can be determined as the result of an iterative Sum of Squared Error minimization problem that can be solved numerically by iterating on a solution. The relatively small range of plausible values for *K* – which depends on the industry classification – makes it possible to iterate on each value and to reach, thus, a global minimum.

III. EMPIRICAL ANALYSIS

The methodology presented in the previous section is applied to the various sectors of economic activity in Greece by using the available data collected from the publications of the National Statistical Service of Greece [16] and the estimates from earlier studies, i.e. [17], [18]. For the industry classification, see Table I. The data are on annual basis and cover the period 1988-1998.

The variables used are the annual growth rates (%) of output: (dY), labor (dL), capital (dK), labor productivity (dl), capital productivity (dk), Total Factor Productivity-T.F.P. (dA), human capital (dH) and technology's contribution (%) to economic growth (π). Using *K*-means algorithm, the Euclidean distance and the relevant minimization algorithm we partition these variables into distinct clusters. See Table II.

Concentration on clusters' performance hides interesting variations. The first cluster experiences a slightly negative annual rate of growth in T.F.P. which, given the very high contribution of technology in economic growth, has prevented the annual output growth rate from being high. This very low growth rate is mainly due to the dramatic capital decrease and not to the increase in labor. The second cluster experiences the lowest contribution of technology-driven growth. Thus, despite the slightly negative TFP growth rate, the significant increases in labor, physical and human capital have led to a significant increase in production. Finally, the third cluster presents a significant dependence upon technology, a negative change in TFP but a positive and significant growth rate in output, whereas human capital remains practically unchanged. Meanwhile, it experiences a high annual growth in capital and labor which have contributed to the cluster's growth.

TABLE I

SECTOR CLASSIFICATION FOR GREECE (1988-1998)

Sector	Description	I.S.I.C. rev.2
1	Agriculture, forestry and fishing	1
2	Mining	2
3	Food, Beverages and Tobacco	31
4	Textiles, apparel and leather	32
5	Wood products and furniture	33
6	Paper, paper products and printing	34
7	Petroleum and coal products	353+354
8	Industrial chemicals, Rubber and Plastic Products	351+352–3522+355+356
9	Non-metallic mineral products	36
10	Iron and steel, non-ferrous metals	371+372
11	Metal products	381
12	Shipbuilding and other transport, motor vehicles, aircraft, electrical apparatus, non electrical apparatus, professional goods, other manufacturing	382–3825+383+3832+3841+3842+3844+3849+3843+3845+385+39
13	Electricity, gas and water	4
14	Construction	5
15	Wholesale and retail trade	61
16	Hotels and restaurants	62
17	Transport, storage and communication	71+72
18	Finance and insurance	81
19	Real estate and business services	82
20	National defense and public administration	-
21	Communication, social and personal services	9

It is evident that the twenty-one clusters of economic activity in Greece formed three (3) clusters and the estimated clusters are, in general terms, consistent with the general structure of the economy into three main clusters (i.e. primary, secondary, and tertiary). Also, the limited growth potential of the first cluster is, at least partly, due to the low growth rate in sectoral investments (1.59%) when compared to the other two clusters' performance (2.36% and 2.22% respectively).

However, although the clustering method is relatively easy to understand, the same is not always true of the results [19]. Accordingly, caution is needed when interpreting the results because it is difficult to manage all the mechanisms involved in cluster formation. In our case, it is worthwhile to emphasize that the results do *not* depend on the following factors: (a) the notion of distance, (b) the linkage method, (c) the number of observations or (d) the number of variables used. All these were confirmed empirically; after changing the factors (a) - (d), the results remained practically unchanged, indicating great cluster stability.

IV. CONCLUSION

In this paper we used the Cluster Analysis methodology to group the various sectors of economic activity in Greece based on their technology and growth characteristics. The twenty-one sectors of economic activity were thus assembled into clusters presenting similar technology and growth characteristics. The results showed that the various sectors of economic activity tended to form three (3) distinct clusters experiencing similar characteristics within each cluster and are consistent with the structure of the economy into three main sectors (i.e. primary, secondary, and tertiary).

The findings in the present paper have important impacts for policy issues. In case the Greek government wishes to support the weakest economic sectors, our analysis pinpoints the cluster, the performance of which is poor and needs enhancement. For instance, the empirical results suggest that the first cluster is a very good option because it demonstrates a high dependence upon technologically induced economic growth and low output and labor growth. In case this cluster could be made to achieve positive technological change, the result would be satisfactory. Therefore, any financial project which aims to support technology should allocate funds more in the first cluster than in the others.

Another interesting finding is that the third cluster, consisting of two major service industries, experiences a very high growth rate followed by a considerable growth rate in labor and an even greater increase in physical capital. However, in spite of the considerable increase in labor, the human capital has slightly decreased implying a lower – practically unchanged – level of labor.

TABLE II

CLUSTER ANALYSIS RESULTS FOR GREECE (1988-1998)

Variable	Cluster 1 (1,2,3,4, 5,7,8,10,11)	Cluster 2 (6,9,12,13,14,15,16, 17,18,20)	Cluster 3 (19,21)
π	75.56	9.58	25.94
dA	-0.30	-0.18	-1.84
dY	0.18	4.70	7.06
dH	2.15	2.40	-0.08
dL	3.03	4.34	9.12
dK	-7.90	7.65	40.65
dI	-2.87	0.36	-2.07
dk	8.07	-3.71	-33.60

Regarding policy formulation, another important finding is that the clustering of sectors is not very responsive to the factors of the model (e.g. metric distance, linkage algorithm, variables, etc). Meanwhile, the specific formation of clusters seems to be supported by the investment activity in the country over, roughly speaking, the same period, and taking into account the time lag before an investment becomes productive.

In this context, our methodology focused on the effect of a variety of variables such as employment, technological change, etc on the formation of clusters. However, a number of additional variables could be used to extend our model in order to account for different characteristics of the local economies. Such variables could be the size of firms, the market structure, the existence of metropolitan areas, etc. However, the lack of comparability in methodology and time period hampers multi-country analyses of technology clustering. We believe that more extended research on the subject would be of great interest.

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